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Joint reconstruction of CO2 plumes using disparate data

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Joint reconstruction of CO_2 plumes using disparate data

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Abstract

We have analyzed various sensor deployment scenarios that maybe used to monitor CO_2 injection as part of the Southeast Regional Carbon Sequestration Partnership (SECARB), Gulf Coast Stacked Storage Project. This scoping study used a stochastic inversion technique to reconstruct the subsurface CO_2 plume using as input several types of data. The technique used, Monte Carlo Markov chain (MCMC), jointly inverted borehole temperature data, downhole tilt data, crosswell resistivity data, crosswell seismic velocity tomograms, and injected CO_2 volume data. The study assumes that the measurements are made using two observation wells that are coplanar with the injector well. The study suggests that the MCMC approach can be used to formally integrate all of the types of data considered, including production and injection data. It also suggests that it is possible to obtain to reasonable plume reconstructions when any one of the cross-well methods is used in combination with temperature logs and injected CO_2 volume data. Finally, the 3D fidelity of the plume reconstruction is highly sensitive to the observation well geometry. The 2D well geometry considered here predicts the 3D geometry of plumes poorly. This approach can be applied to any large injection project, including commercial efforts and the phase III demonstrations.

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Introduction:

Monitoring and verification of CO2 in the subsurface remains an important task for geological CO2 storage. This will likely involve the collection and integration of multiple geological, geophysical, and geochemical data sets within the context of some reservoir model. We have developed a computational tool to more realistically render subsurface liquid plumes (e.g., CO_2, steam, water floods, tank leaks) and their reservoirs using multiple geophysical techniques.

In this study, we have analyzed various sensor deployment scenarios that maybe used to monitor CO_2 injection as part of the Southeast Regional Carbon Sequestration Partnership (SECARB), Gulf Coast Stacked Storage Project (GCSSP), Cranfield site. This proof of concept test seeks to demonstrate that the stochastic inversion approach used will successfully integrate the disparate data types that may be collected during the GCSSP. The test results show how well the 3D geometry and $C0_2$ volume can reconstructed for the various sensor packages considered.

We assumed two observation wells at the Cranfield site, coplanar with the injector well (refer to Figure 1). This well arrangement was chosen in consultation with Tom Daly

(Lawrence Berkeley National Laboratory). It maximizes the ability to track the growth of the plume with time up-dip from the injector well. The sensitivity and resolution using this arrangement is largely two dimensional: the length and vertical extent of the plume can be resolved but the off-plane shape and the width of the plume cannot be determined uniquely.

Figure 1 shows that two plume sizes were considered. We assumed that the CO_2 plume grew as function of time and that time-lapse data is available. The plume's thickness, horizontal and vertical extent increases as additional CO_2 is injected. The two plumes contain 664 and 7538 m3 of CO_2. The average CO_2 saturation for both plumes is 40%. The center of mass for each plume is located at a depth of 3050 m.

Our test assumes that the following measurements will be made during the injection test:

injected $C0_2$ volume

temperature logs collected within the two observation wells in the depth range 3000 – 3090 m.

tilt surveys collected using a total of 18 sensors located in the two observation wells on a 3 m spacing; the sensors are located in the depth range 3009 – 3081 m .

seismic tomogram of P velocity changes that has been converted into a map of CO2 saturation using a suitable petrophysical model; the tomogram extends from the injector to observation well 2, and from depth 3009 to 3081 m. The pixels on the tomograms are 3 by 3 m.

crosswell electrical resistivity surveys collected using a total of 27 electrodes located outside of the injector and observation wells using a 3 m spacing; the electrodes are located in the depth range 3009 to 3081 m.

The crosswell techniques (seismic, resistivity and tilt) will exhibit the greatest sensitivity and resolution to parts of the plume between the injector and observation well 1. The sensitivity and resolution between the two observation wells is much worse due to the greater distance between the plume and the sensors.

We consider the results of this test preliminary. A full analysis of the results could not be conducted due to tight budget constraints. Many of our assumptions are overly optimistic: a) measurement uncertainty is considered negligible, and b) the uncertainty associated with converting each plume realization from CO_2 saturation to various the observables such as temperature, P wave velocity and tilt is assumed to be negligible. These uncertainties are not well understood and require further research.

<u>Conversion of CO_2 saturation to the various observables</u>

We assume that a CO_2 plume can be represented by a series of contiguous blocky regions that are:

embedded within a porous medium

either connected or adjacent to the other plume regions,

one of the blocky regions is near the injector well

each blocky region has constant co2 saturation in the range 0 to 100%.

Our stochastic approach proposes randomly chosen CO_2 saturation models that are tested against all available data. This means that we need to convert each plume realization from CO_2 saturation to some other dimension (e.g., reservoir deformation, temperature, bulk electrical resistivity).

We use Archie's equation to convert the CO_2 saturation model to an electrical resistivity model. We assume that the CO_2 does not change the electrical properties of the native pore water or the silicate substrate, and that temperature changes in the reservoir do not significantly affect its electrical resistivity; we do not know how valid this assumption is. The electrical resistivity model is used to solve the forward problem and calculate the resistivity data predicted for each plume model. This calculation is the most computer-intensive part of our method. Specifically, the runs that used resistivity data required the use of 216 CPUs running for 12 hours in a large parallel cluster.

To compare each CO_2 saturation model to a measurement of injected CO_2 volume we assume that the connected porosity in the reservoir is 25% on average.

We assume that the temperature will decrease from 125 to 124.8 C as the CO_2 saturation changes from 0 to 100%. This allows us to directly compare the temperature measurements and the CO_2 saturation models proposed.

We assume that the bulk pressure changes in the reservoir are directly proportional to the CO_2 saturation of the reservoir layer. This allows us to convert the CO_2 plume model to a reservoir deformation model (used to solve the tilt forward problem). The predicted and observed tilt data can then be compared. We recognize that there is significant uncertainty in this conversion because CO_2 saturation – pressure relationship is not well known, and it is possible that the correlation between the two is poor. This issue will be addressed in future tests.

The changes in P velocity detected by seismic tomography are converted by to CO_2 saturation using a suitable petrophysical model such as a modified Gassman model that assumes that CO_2 saturation occurs in patches. We assume that the tomogram recovers the changes in P velocity without distortion. We also assume that the conversion from P velocity change to CO_2 saturation is error-free. The uncertainties associated with this conversion are not well understood and are being evaluated by ongoing research (Tom Daily, LBNL, personal communication). The estimated CO_2 saturation map is used as input to the MCMC inversion and directly compared to the CO_2 saturation in the proposed plume models.

Description of stochastic inversion approach:

A detailed description of our stochastic inversion approach can be found in Ramirez et al., 2005. Here we present some of the key ideas. The tool uses statistical theory and geophysical forward models to compute images of the subsurface CO_2 plumes. It produces plume images that are consistent with disparate data types such as measurements of injected plume CO_2 volume, ground deformation measurements (tilt, gps, InSAR), and cross-borehole electrical resistivity measurements. Joint reconstruction of these data allows better plume images to be computed. Our reconstruction method uses Bayesian inference, a probabilistic approach that combines observed data, geophysical forward models, and prior knowledge (e.g., measurements of the injected CO_2 volume, knowledge that the plume should connect to injector). The result is a sample of the likely plume models that are consistent with the data collected. The method uses a Markov Chain Monte Carlo (MCMC) technique to sample the space of possible plume models, including the shape, location and CO_2 content of the plume. MCMC is a proven technique that uses a random-walk type procedure to sample possible outcomes given all available data.

Attractive features of this approach are:

- *Joint Reconstructions*: Results are consistent will all available data. Disparate data types such as surface tilt, electrical resistivity, and tilt showing likely permeable pathways are simultaneously used to compute the results.
- *Realistic models*: Geophysical inversion is typically an ill-posed problem requiring regularization. The SE is stabilized by prior information instead of the often unrealistic regularization techniques (e.g. smooth models) used by traditional inversion approaches.
- *Estimates of uncertainty*: The method provides quantitative measures of the result uncertainty.
- *Alternative models*: The SE will identify competing models when the available data is insufficient to definitively identify a single optimal model. The SE will also provide the probability that a given model is the best explanation for the available data.
- *Sensitivity*: The unique sensitivity of each data type is preserved and formally included in the analysis. For example, electrical methods are very sensitive to pore fluid character and surface deformation measurements are sensitive to reservoir pressure changes caused by the injected fluid.

Results and Discussion

Our tests considered various combinations of instrumentation packages that could be deployed to monitor the CO_2 plume during the GCSSP. The simplest package may consist of temperature sensors (or logs) deployed in the observation wells and a flowmeter in the injector well that measures injected CO_2 volume. A more complex package may include additional measurements such as crosswell seismic, crosswell resistivity, and downhole tilt sensors. In all our simulations, we assumed that injected CO_2 volume and borehole temperatures were always measured because these measurements are relatively cheap and easy to make. Other simulations included various combinations of the crosswell techniques (seismic, resistivity, tilt).

As expected the best results are obtained where two of the crosswell techniques are deployed simultaneously with temperature surveys and injected volume. Figures 2a,b and 3 a,b show results that illustrate this.

The figures show map and side views of the two best plume models, i.e., the models that best fit all the available data; the model on top fits the data somewhat better. The MCMC inversion approach identifies and ranks competing models when the available data is insufficient to definitively identify a single optimal model.

The diagram on the top left indicates the different types of data used for the run; for example, the results in Figures 2a,b were reconstructed using CO_2 saturation tomography-seismic, crosswell resistivity, temperatures and injected volume data. The dimensions of the 3D block that contains the plume model are shown in Figure 1. White dots (map view) and vertical lines (side view) indicate the well locations. The outline of the "true" plume is shown by the ellipse and rectangle (map and side view, respectively). The color of the plume indicates the CO_2 saturation level (40% in the "true" plume, indicated by an aqua color). The figures also show the total CO_2 volume present within each plume; for the small and large plumes, the "true" volumes are 664 and 7538 m^3.

Figures 2 and 3 indicate that the length and vertical extent of the plume are recovered reasonably well along the plane defined by the wells. Also, the estimated total CO_2 volumes are within 35% of the "true" model for the larger plume (Figs. 2a, 3a). For the smaller plume (Figs. 2b, 3b), the estimated total CO_2 volumes are within 300 % of the "true" model. The off-plane shape and size of the plume is not recovered well because the coplanar well arrangement does not offer the coverage required to resolve the plume in the off-plane direction.

The remaining figures show results that use fewer measurement techniques. For example, Figure 5a,b shows the models estimated using downhole tilt, temperature and injected volume data. The shape and size of the plume in 5a are similar to those in Figure 3a where the measurement package also included the CO_2 saturation tomogram based on seismic velocity differences. This suggests that one may get reasonable results obtained using just one crosswell technique (tilt) instead of two (tilt and CO_2 tomography-seismic). This conclusion needs to be considered preliminary because the uncertainties associated with each of these techniques has been assumed to be negligible and we know that this is overly optimistic. Similar comments can be made regarding Figures 4a and 2a where crosswell resistivity and seismic data are considered.

Summary:

We have performed numerical simulation experiments to evaluate various sensor deployment scenarios that maybe used to monitor CO_2 injection as part of the GCSSP. We have used a stochastic inversion technique to reconstruct the subsurface CO_2 plume using several types of data: temperature data, downhole tilt data, crosswell resistivity data, crosswell seismic velocity tomograms, and injected CO_2 volume. The results of the study suggest that the stochastic inversion approach can be used to formally integrate all of the types of data considered.

The study assumes that there will be two observation wells at the GCCSP's Cranfield site that are coplanar with and updip from the injection well. The results indicate that this well arrangement provides the sensitivity/resolution needed to reconstruct the 2D characteristics of the plume along the plane defined by the wells. Also, the time evolution of the plume updip from the injector can be successfully monitored with this arrangement. However, the off-plane plume characteristics are reconstructed poorly.

The study suggests that it is possible to obtain to reasonable plume reconstructions when any one of the cross-well methods is used in combination with temperature logs and injected CO_2 volume data.

The results and conclusions of this study are preliminary because many of the assumptions are overly simplistic and optimistic. In particular, the uncertainty associated with converting each plume realization from CO_2 saturation to various the observables such as temperature, P wave velocity and tilt needs to be properly understood and included in the modeling. This aspect will be addressed in future research.

Figures

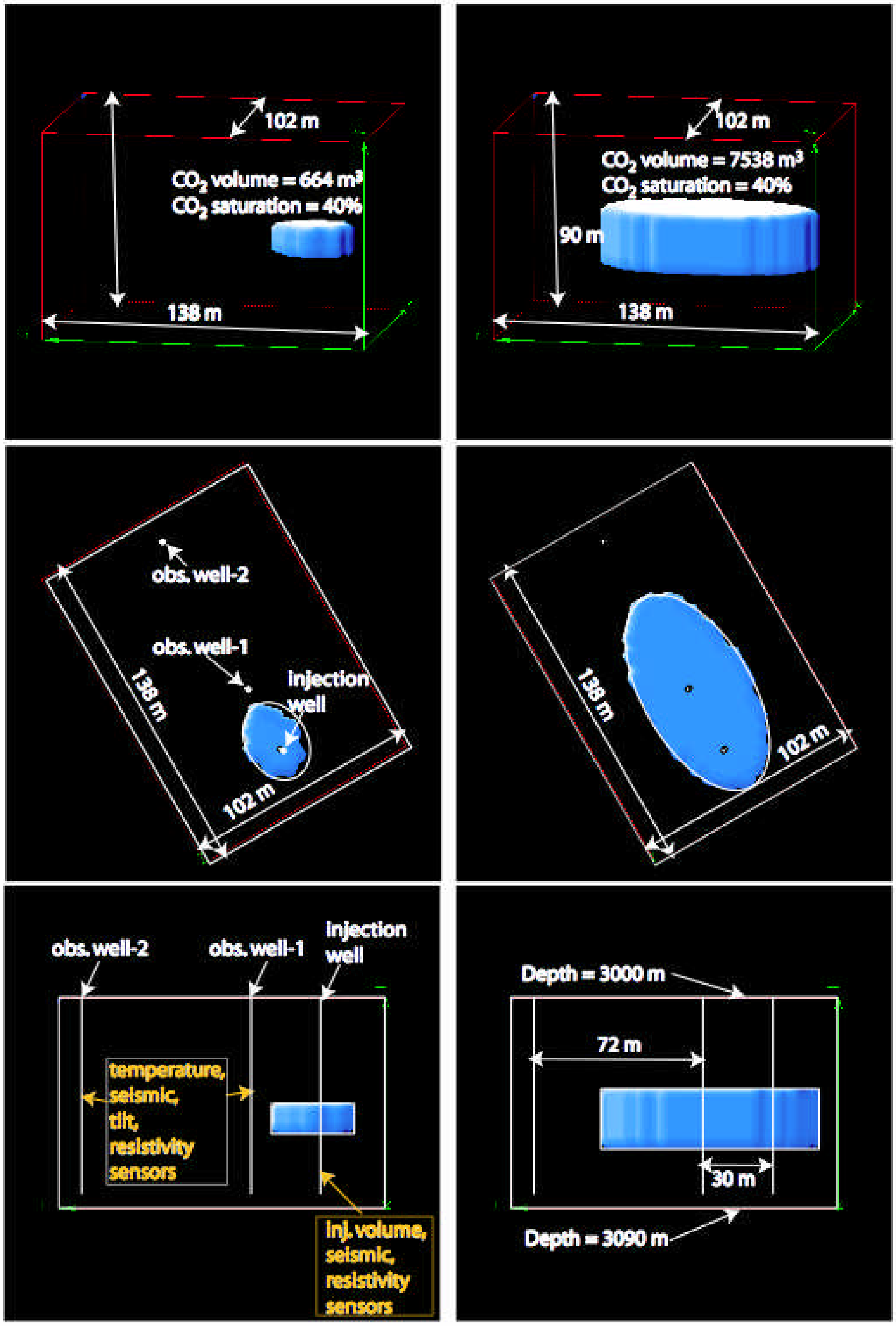

Figure 1 shows details of the two plume models used for this test. The CO_2 saturation within each plume is 40%.

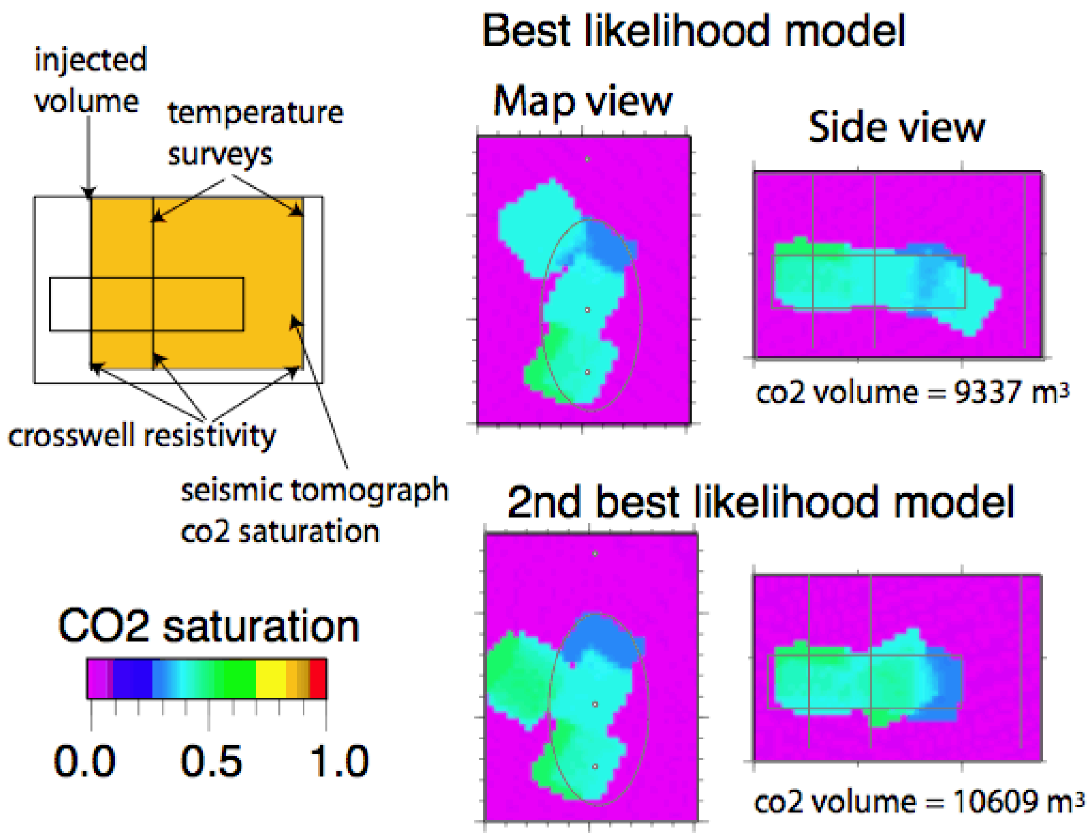

Figure 2a shows the two plume models (large plume) that best fit all of the following data sets: temperature logs, CO_2 injection volume, cross-well resistivity data and a tomograpm of CO_2 saturation based on seismic P velocity changes. The outline of the "true" plume, the location of the wells and the estimated CO_2 volume associated with both plume models are shown.

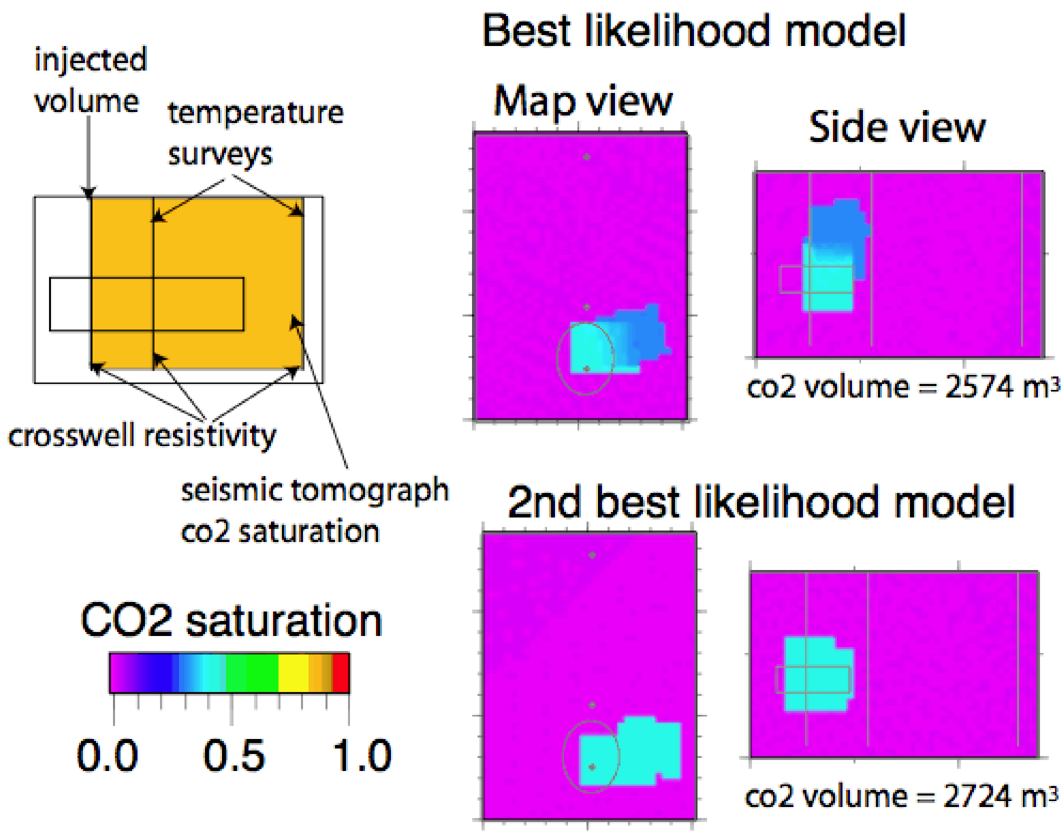

Figure 2b shows the two plume models (small plume) that best fit all of the following data sets: temperature logs, CO_2 injection volume, cross-well resistivity data and a tomogram of CO_2 saturation based on seismic P velocity changes. The outline of the "true" plume, the location of the wells and the estimated CO_2 volume associated with both plume models are shown.

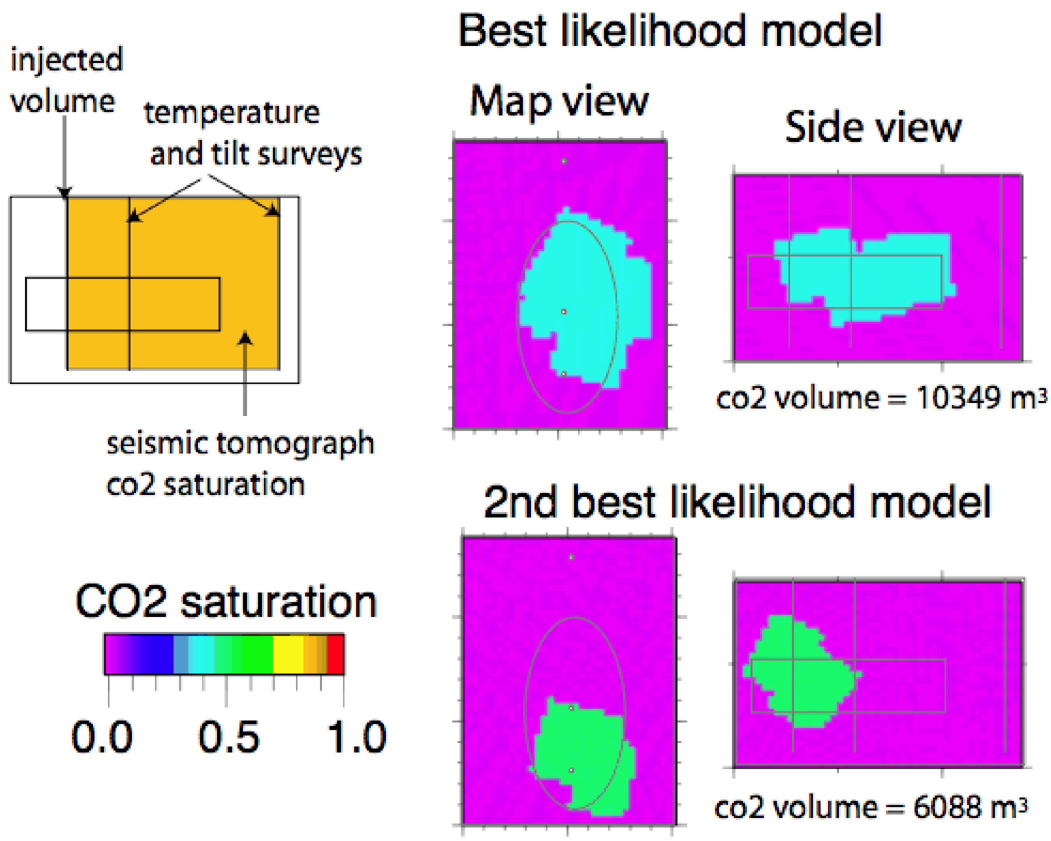

Figure 3a shows the two plume models (large plume) that best fit all of the following data sets: temperature logs, CO_2 injection volume, a tomogram of CO_2 saturation based on seismic P velocity changes, and downhole tilt.

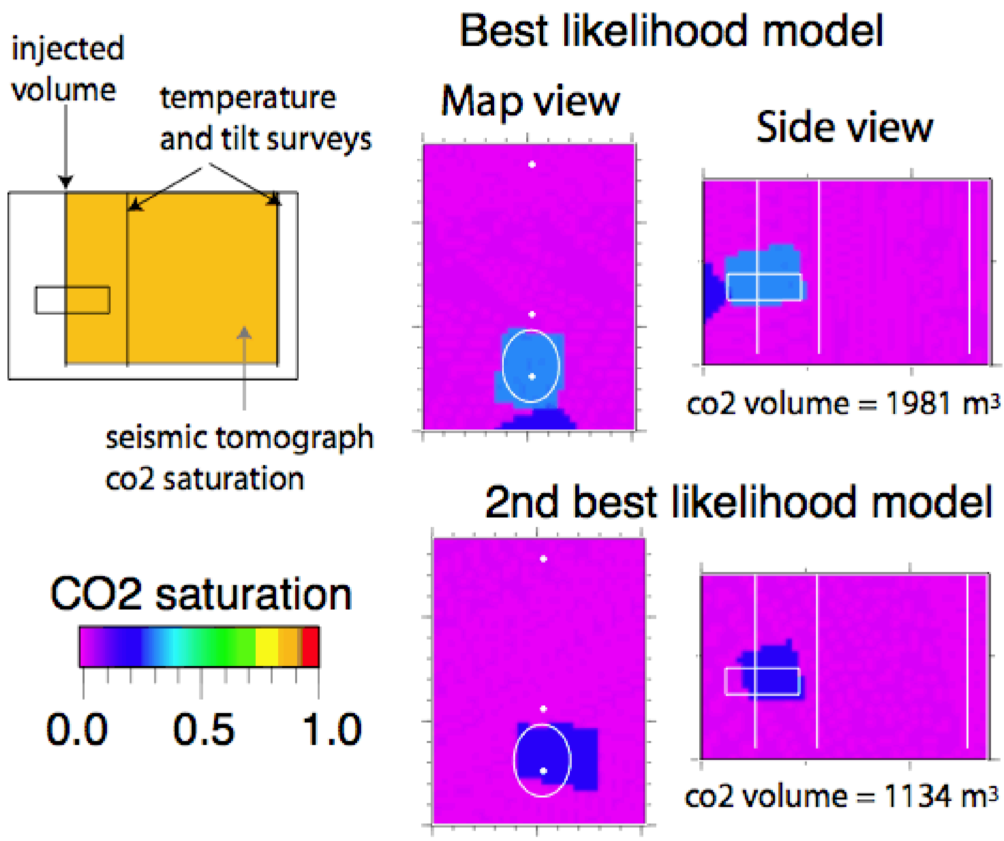

Figure 3b shows the two plume models (small plume) that best fit all of the following data sets: temperature logs, CO_2 injection volume, a tomogram of CO_2 saturation based on seismic P velocity changes, and downhole tilt.

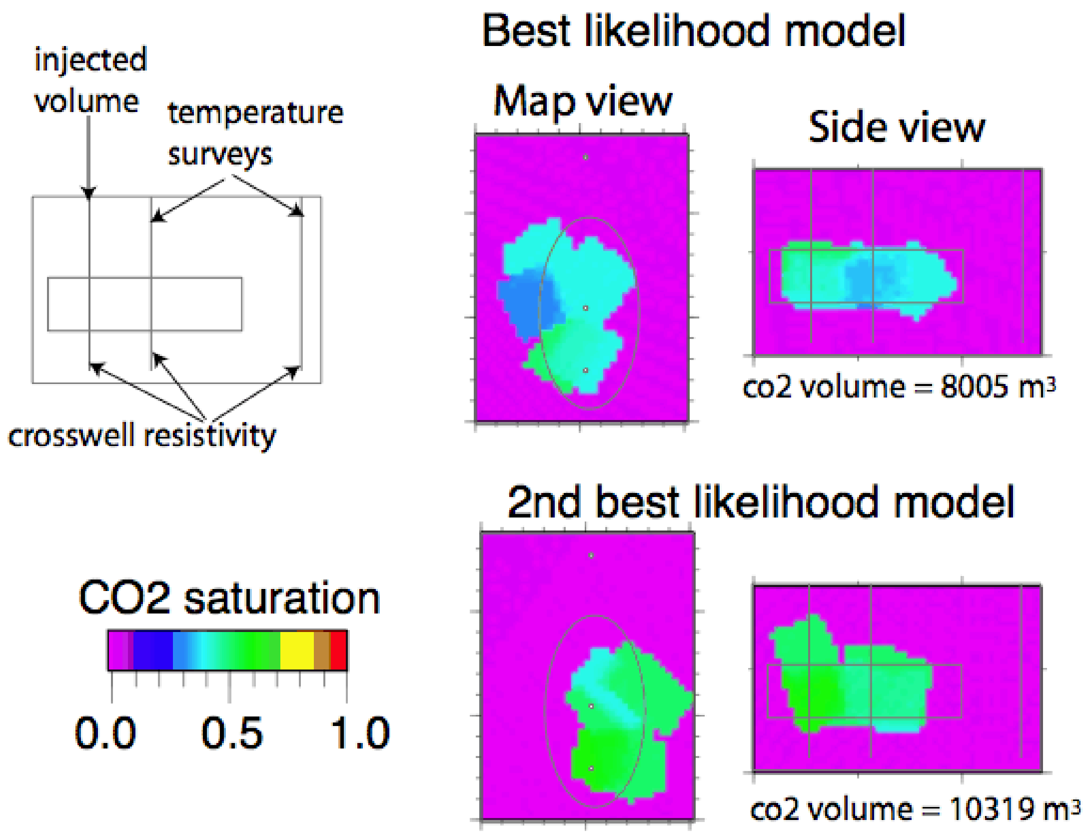

Figure 4a shows the two plume models (large plume) that best fit all of the following data sets: temperature logs, CO_2 injection volume, and crosswell resistivity.

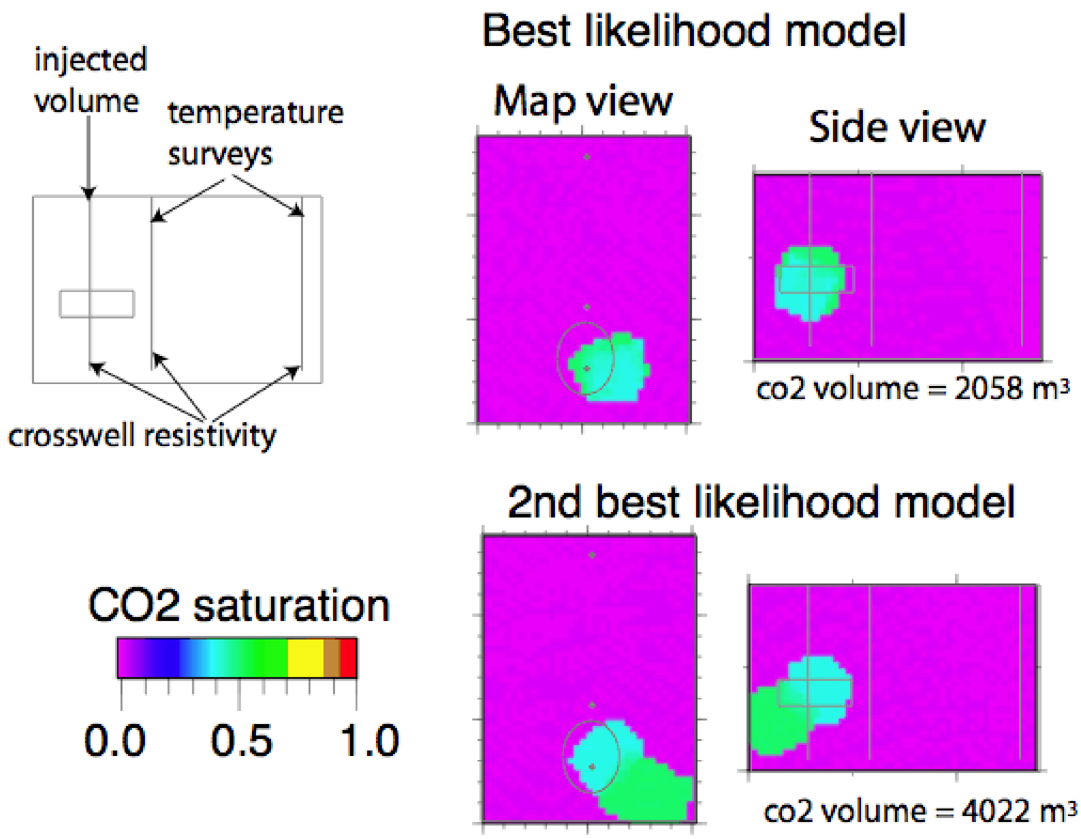

Figure 4b shows the two plume models (small plume) that best fit all of the following data sets: temperature logs, CO_2 injection volume, and crosswell resistivity.

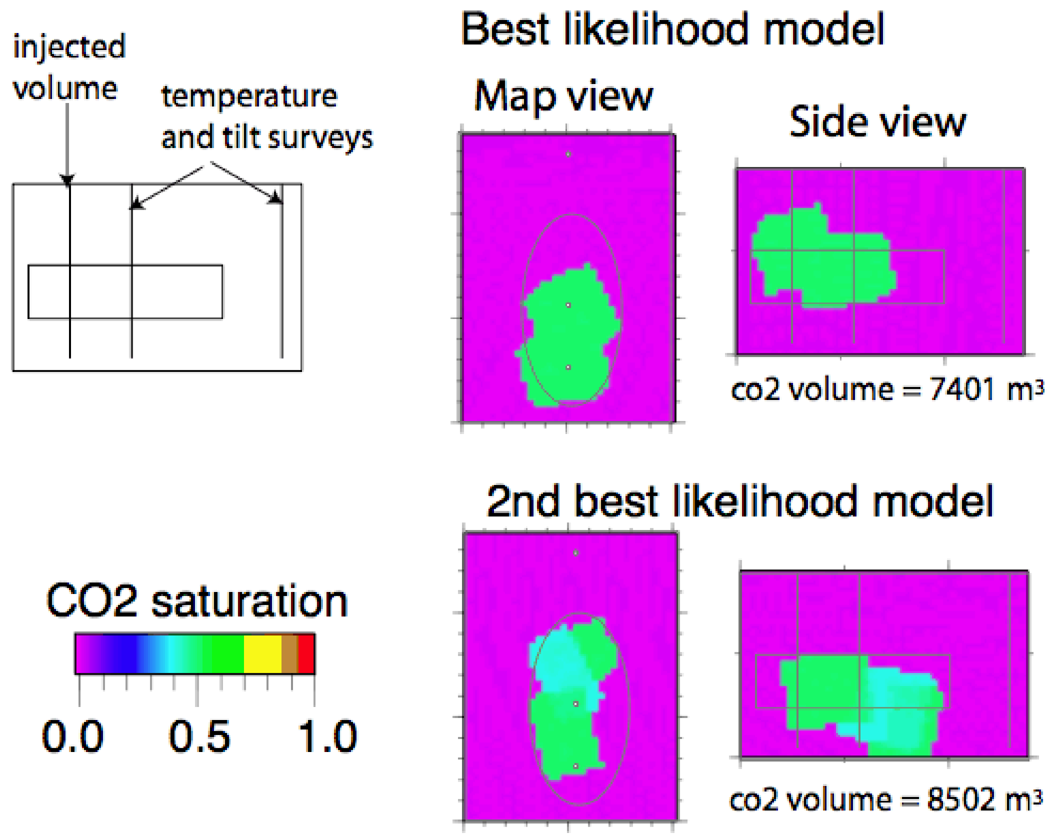

Figure 5a shows the two plume models (large plume) that best fit all of the following data sets: temperature logs, CO_2 injection volume, and downhole tilt.

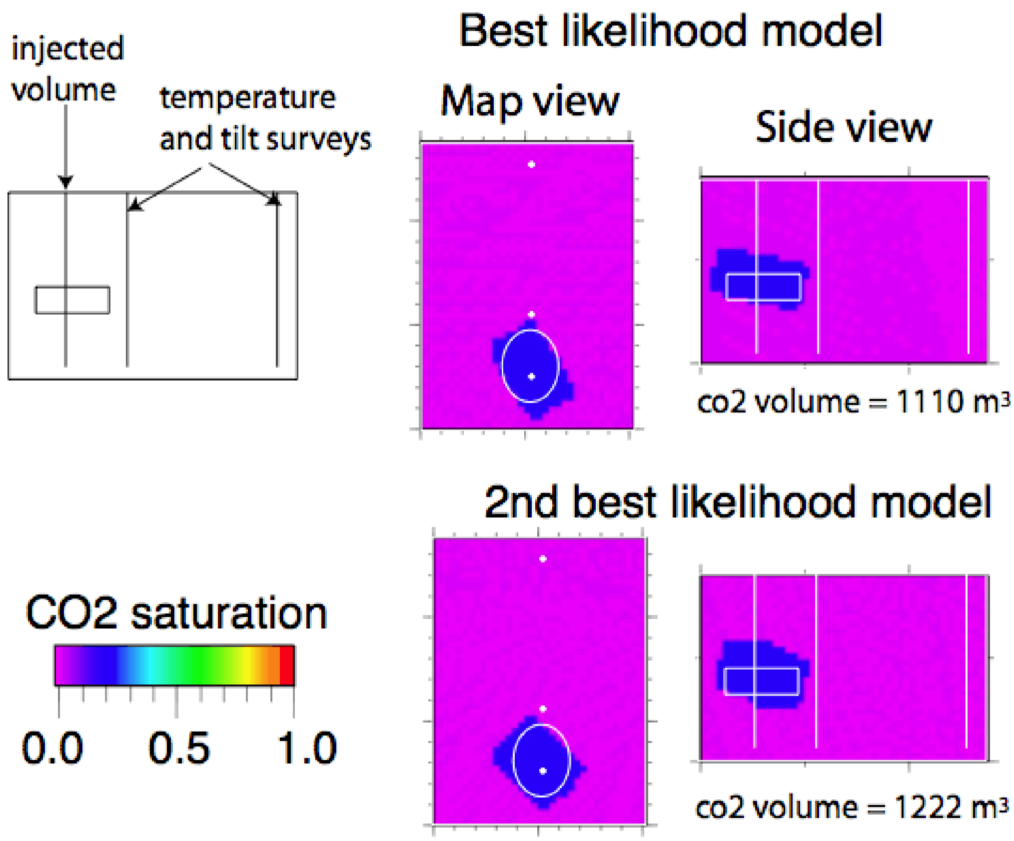

Figure 5b shows the two plume models (small plume) that best fit all of the following data sets: temperature logs, CO_2 injection volume, and downhole tilt.

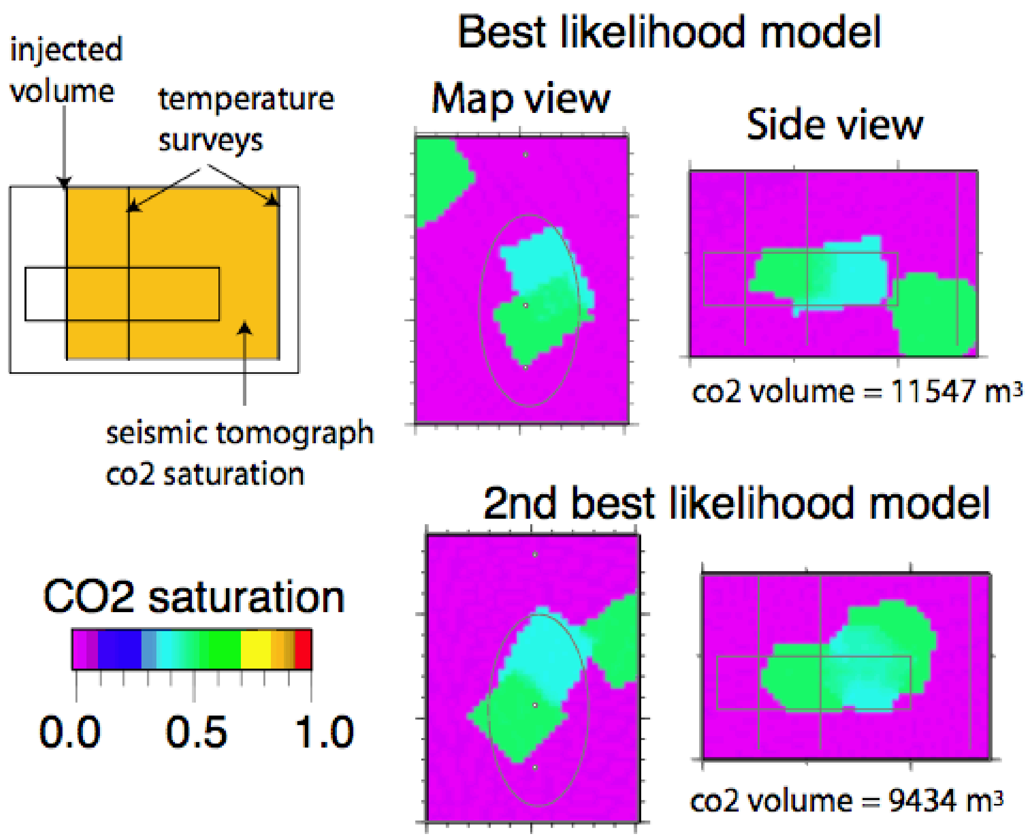

Figure 6a shows the two plume models (target: large plume) that best fit all of the following data sets: temperature logs, CO_2 injection volume, and a tomogram of CO_2 saturation based on seismic P velocity changes.

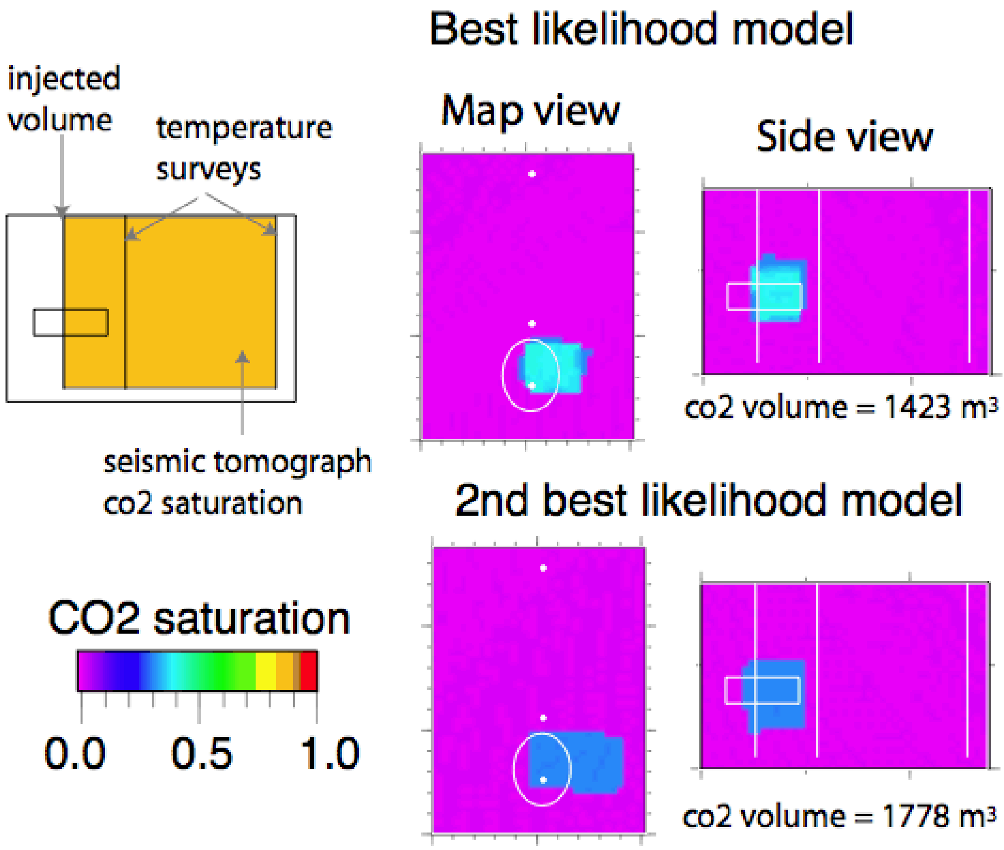

Figure 6b shows the two plume models (target: small plume) that best fit all of the following data sets: temperature logs, CO_2 injection volume, and a tomogram of CO_2 saturation based on seismic P velocity changes.

References:

Ramirez, A. L., J.J. Nitao, W.G. Hanley, R.D. Aines, R.E. Glaser, S.K. Sengupta, K.M. Dyer, T.L. Hickling, W.D. Daily, 2005, Stochastic Inversion of Electrical Resistivity Changes Using a Markov Chain, Monte Carlo Approach, *Journal of Geophysical Research,* vol. 110, B02101, doi:10.1029/2004JB003449.